WAVES AND WAVELETS: AN AUTOMATED DETECTION TECHNIQUE FOR SOLAR OSCILLATIONS

I. DE MOORTEL[1] and R. T. J. McATEER[2]
[1]*School of Mathematics and Statistics, University of St Andrews, North Haugh, St Andrews, Fife KY16 9SS, Scotland (e-mail: ineke@mcs.st-and.ac.uk)*
[2]*National Research Council Research Associate, NASA Goddard Space Flight Center, Solar Physics Branch, Code 682, Greenbelt, MD 20771 (e-mail: j.mcateer@grasshopper.gsfc.nasa.gov) Previous address: Department of Pure and Applied Physics, Queen's University Belfast, Belfast, BT7 1NN, N.Ireland*

(Received ; accepted)

Abstract. This paper investigates the possibility of automating the detection of propagating intensity perturbations in coronal loops using wavelet analysis. Two different sets of TRACE 171 Å images are studied using the automated wavelet routine presented by McAteer *et al.* (2004). Both localised, short-lived periodicities and sustained, periodic, oscillations are picked up by the routine, with the results dependent to a large extend on the signal-to-noise ratio of the dataset. At present, the automation is only partial; the relevance of the detected periodicity and the identification of the coronal structure supporting it still have to be determined by the user, as does the judging of the accuracy of the results. Care has to be taken when interpreting the results of the wavelet analysis, and a good knowledge of all possible factors that might influence or distort the results is a necessity. Despite these limitations, wavelet analysis can play an important role in automatically identifying a variety of phenomena and in the analysis of the ever-growing (observational or simulated) datasets.

1. Introduction

The number of direct observations of oscillations in the solar corona has risen dramatically in recent years, due to the increased resolution of space-based missions such as SOHO and TRACE. Most of these wave-like motions observed in the solar atmosphere are not steady harmonic waves but tend to exist for only a few periods and are of finite lifetime. Wavelet analysis is a powerful technique which allows a local decomposition of timescales in the timeseries, and therefore, is ideal for analysing such non-stationary timeseries or timeseries where one expects localised variations of power. Over the last decade or so, wavelet analysis has become an increasingly popular method to analyse a wide variety of solar observations. For example, Bocchialini and Baudin (1995) examined the frequency and duration of chromospheric quiet-Sun velocity oscillations, whereas Baudin *et al.* (1996) used wavelet analysis to examine upward propagating waves, which emerge from the chromospheric network. Molowny-Horas *et al.* (1997) analyse both the periodicity and oscillation lifetime of Doppler oscillations in a quiescent, solar prominence, whereas Ireland *et al.* (1999) study active region oscillations. More recently, Mc-

Solar Physics **0:** 1–12, 2004.

Ateer *et al.* (2003) studied oscillations in network bright points, Christopoulou *et al.* (2003) investigated the temporal behaviour of intensity and velocity umbral oscillations in the chromosphere and Ugarte-Urra *et al.* (2004) studied spectral data of bright points. McIntosh and Smillie (2004) suggest that wavelet analysis can be useful in identifying chromospheric oscillations both temporally and spatially with their photospheric sources. The above are but a few examples of the use of wavelet analysis in a solar context, and many more can be found in the literature. However, the wavelet technique must be applied with great care and all the possible factors that could affect the transform must be kept in mind when interpreting the results (De Moortel *et al.*, 2004).

The long lifespan and improved telemetry of current (and future) missions provides such a large amount of observational data that automated detection routines become a necessity. Additionally, the study of large datasets (both in area and duration) is needed to improve the statistics of current results, with regards to various kinds of coronal oscillations as well as localised, short-lived events. Wavelet analysis can play an important role in this process, as it is capable of identifying not only periodicity present in a given data set, but also provides time localisation. Therefore, it is possible to use wavelet analysis to (automatically) detect and distinguish between short-lived, isolated perturbations (e.g., nanoflares or blinkers) and coherent, sustained oscillatory perturbations.

The primary aim of this paper is to test whether the automated wavelet routine of McAteer *et al.* (2004) is capable of detecting long-lived intensity disturbances, observed in coronal loops. We will investigate the presence of oscillations in TRACE 171 Å observations, using this wavelet routine. The data used in this paper were taken on 9 April 2000 (13:54 UT) and 13 June 2001 (06:46 UT), as part of JOPs 83 and 144, respectively. Analysing these high-cadence datasets, De Moortel *et al.* (2002) (Paper I) discovered quasi-periodic intensity variations, propagating along the lower part of large coronal loops, which were interpreted as slow magneto-acoustic waves (their examples 6a, 17c, and 17d). Such propagating intensity oscillations appear to be a widespread, coronal phenomenon (Berhmans and Clette, 1999; Robbrecht *et al.*, 2001; De Moortel *et al.*, 2002; King *et al.*, 2003), and hence, are a prime candidate to test the automated wavelet routine. The detection routine is outlined in Section 2, the results for both datasets are described in Section 3 and a discussion and conclusions are given in Section 4.

2. Detection Routine

The code we are using in this study was develloped by McAteer *et al.* (2004). For a given datacube, the code performs a wavelet analysis of the timeseries in each pixel and outputs the periodicities that are present in these timeseries, the duration of the detected periodicities, as well as their start and end time.

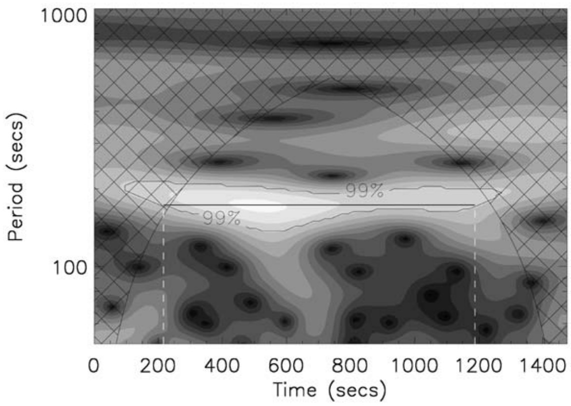

Figure 1. Typical example of a wavelet transform, plotting periodicity (on a log scale) against time, where brighter colours correspond to higher power. The hatched area indicates the COI. The lifetime of the periodicity detected above the 99% confidence level is indicated by the *horizontal black line* and *dashed white lines*.

The wavelet analysis in the code of McAteer *et al.* (2004) is performed using the routine of Torrence and Compo (1998) and the automated detection of oscillations is based on a procedure first presented by Ireland *et al.* (1999). The procedure is illustrated in Figure 1 (or see Figure 2 of McAteer *et al.*, 2004). Firstly, the periodicity of power maxima, above a certain confidence level, is identified (e.g., horizontal black line). Subsequently, the duration of each periodicity, again above the confidence level, is determined (dashed, white lines). To be counted as an oscillation, this duration of a detected periodicity P has to be longer than $\sqrt{2}P$ when using the Morlet mother wavelet or $P/\sqrt{2}$ for the Paul wavelet (Torrence and Compo, 1998; McAteer *et al.*, 2004). The wavelet transform of a finite signal suffers from errors at the edges of the transform and the region where these errors may be important is known as the cone-of-influence (COI), indicated as the hatched region in Figure 1. Portions of the transform inside this hatched area are subject to these edge effects and should be treated with caution. When calculating the duration of an oscillation, there are two possible options with regard to the COI: ignore all power that falls inside the COI, or allow for (some) power to be inside the COI (remember that the *maximum* power has to fall outside the COI). The first option leads to a lot of ‘false’ detections where the start and end times basically coincide with the limits of the COI. This is not an incorrect result but at the same time, does not really say much about the true duration of the oscillations (as the duration will basically be given by the extend of the COI at that specific periodicity). The second option has a similar problem in the sense that it leads to a lot of start and end times that coincide with the start and end of the timeseries. Additionally, the wrap-around of the timeseries in the wavelet code makes it unclear where exactly periodicity detected near the edges of the time interval is situated in reality. In this study, we have chosen a modified version of the second option:

power inside the COI is taken into account when calculating the duration of the oscillation, but with the added requirement that the start time must be greater than zero, and the end time smaller than the end of the timeseries. In other words, we work out the duration of ‘closed’ contours of power above the confidence level, but the maximum power must be situated outside the COI. This will introduce a slight dependence of the estimated duration on the amplitude of the oscillation, as large amplitude oscillations are more likely to be detected inside the COI region. Finally, the timing of each periodicity is worked out. Again, there are various options that can be chosen, such as the first or final time at which periodicity is present above the confidence level. Or, as in the rest of this paper, the time at which the maximum wavelet power occurs (peak time).

Various settings of the routine can be altered, such as the confidence level or the mother wavelet and it can be instructive to repeat the detection routine with different combinations of these settings. The results presented in the next section are obtained using the Morlet wavelet and a 99% confidence level. One of the problems of wavelet analysis is that it will identify any form of periodicity, including very short-lived events. Such short-lived events could be associated with real, solar, events, such as blinkers or nano-flares, but could equally be introduced artificially be e.g., spacecraft jitter or cosmic rays. As short-lived, localised events are not the primary interest of the present study, we have smoothed the data with a 5×5 boxcar. This will lower the amplitude of the perturbations and hence, should reduce the number of detections of such small-scale events. Note here that, although the smoothing of the data (i.e. averaging in the spatial domain) improves the signal-to-noise ratio, it does sacrifice some of the spatial resolution. As we are concentrating on long-lived intensity perturbations in large coronal loops, the improved signal-to-noise ratio is preferable above the spatial resolution. However, when using wavelet analysis and/or an automated detection routine for other purposes, the user will have to carefully judge the effects of this trade-off. Finally, we note that the TRACE read-out noise is unlikely to affect our results, as the amplitude of the oscillations described in Paper I is considerable higher than the expected amplitude of the read-out noise (DeForest, priv. commun., 2004).

The final output of the routine is a list of periodicities, the number of cycles for which these were present, and the time at which the maximum of the corresponding wavelet power occurred, for all oscillations in each pixel in the dataset. Getting an overview of the results produced by the routine, or presenting them, can be difficult due to the large number of periodicities that is sometimes identified. One way to deal with this problem is to limit the range of periodicities considered at any one time, and then to repeat this procedure until the whole range of possible periodicities has been covered. This also makes it easier to interpret the results and identify groups of coherent oscillations.

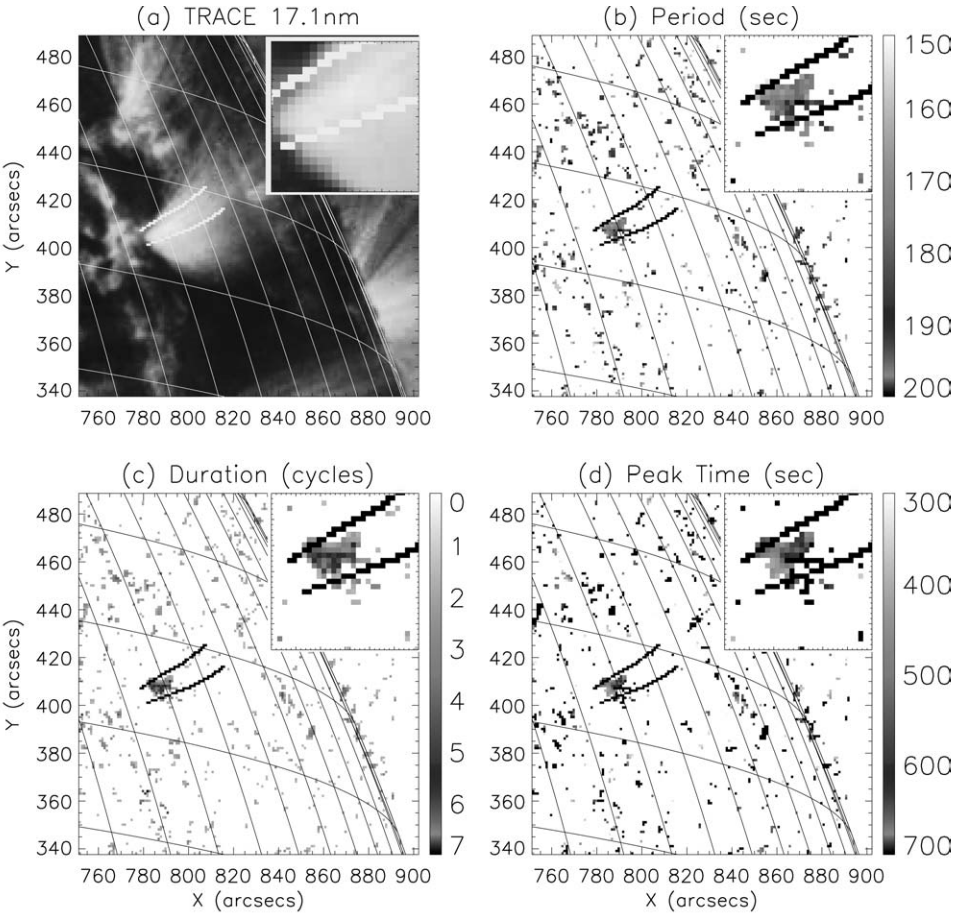

Figure 2. (a) Example (TRACE 171 Å – 9 April 2000, 13:54 UT) of a large coronal loop footpoint supporting an oscillatory signal. (b) Periodicities (in seconds) detected by the wavelet routine in the dataset. (c) The number of periodicity cycles. (d) Peak time at which the maximum wavelet power occurred (in seconds from the start time of the dataset. (Note that the labelling on some of the axes is omitted in order to not needlessly clutter the figures.)

3. Data Analysis

3.1. 9 April 2000

The first datacube we examined is a subset of 166 TRACE 171 Å, 151×151 ($1''$ pixel scale) images, taken at 13:54 UT on 9 April 2000. The oscillation detected in this subset was labelled 'example 6a' in Paper I. The first image of this dataset is shown in Figure 2(a), with the loop supporting the oscillations outlined by the white lines. In Figure 2(b), the periodicities detected by the wavelet routine in the 150–200 s range are displayed, with the supporting loop now marked with black lines. The largest, most coherent 'patch' of periodicity is situated inside this

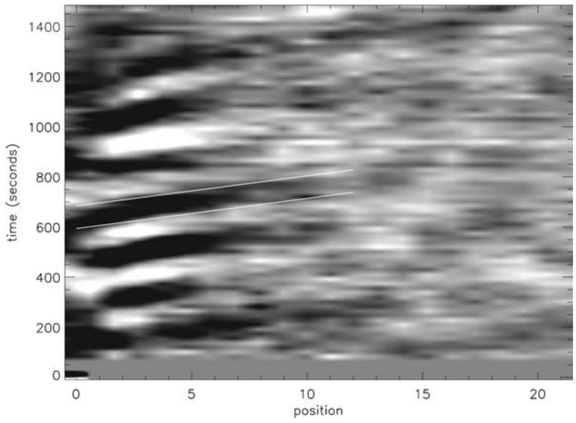

Figure 3. A plot of the running difference between the average time series for each position for the 9 April 2000 (13:54 UT) data.

loop. The detected period is in the range of 170–180 s, which is the same as the periodicity reported in Paper I (175 s). However, the detection of a periodicity does not necessarily imply that a sustained (long-lived) oscillation is present. Indeed, the wavelet analysis detects any form of periodicity, regardless of the number of periodic cycles that is present in the signal. Hence, it is important to investigate the number of cycles, which is shown in Figure 2(c). The only location where a considerable number of periodicity cycles ($\sim 3-6$) occurs, is the lower part of the large coronal loop. This is in good agreement with the number of dark and bright diagonal bands that can be seen in the running difference image for this example (Figure 3). The running-difference was created to emphasise the time-variable behaviour of the loop by subtracting from each frame the frame taken roughly 90 s earlier (see Paper I for more details). An intensity disturbance propagating along the analysed structure can be identified as clear diagonal bright and dark bands in such a running-difference image. Dark bands correspond to regions of lower intensity, whereas bright bands represent a relatively higher intensity. A positive gradient indicates an outward travelling disturbance. At all other locations, only 1–2 cycles of periodicity are present, which implies these are short-lived events, rather than sustained oscillations. Finally, Figure 2(d) shows the time at which the maximum in wavelet power occurred (peak time), given in seconds from the start time of the dataset. Moving away from the loop footpoint, the peak time (roughly) occurs at later times. However, the progressively later start times do not allow us to distinguish between phase and group propagation. To truely identify the long-lived oscillations as outwardly propagating, an additional study, such as creating a running difference is necessary. All other periodicities appear to have more or less random peak times.

As pointed out in the introduction, the main aim of this paper is to test whether the automated wavelet routine of McAteer *et al.* (2004) is capable of detecting

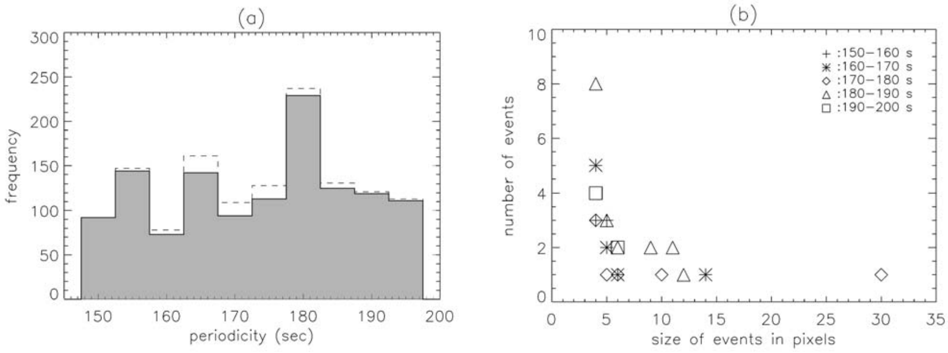

Figure 4. (a) Histogram of the periodicities found in the 9 April 2000 dataset, excluding the periodicties found in the region marked in Figure 2. The dashed line corresponds to the histogram where this region was included. (b) The 'event' sizes, including the marked structure, per periodicity.

long-lived intensity disturbances, observed in coronal loops in Paper I. However, before studying a second datacube, we briefly discuss the small-scale events that are also picked up by the wavelet routine outside the coronal loop that is outlined. As the wavelet analysis detects not only periodicities in a signal, but also their respective time localisation, it it equally well suited to study sustained oscillations as it is to detect relatively short-lived events. Although not the primary object of this study, these small-scale 'patches' of short-lived periodicity could be of considerable interest. Indeed, due to the complex and highly dynamic nature of the solar corona, burst-like events are more likely to occur at almost any given time and location than periodic, long-lived oscillations. Obviously, one would have to identify the origin and nature of the events but in this study, we merely want to demonstrate that they can be detected automatically, using wavelet analysis. As is clear from comparing Figures 2(b–d), a large number of these small-scale periodicities, which only last for a few cycles, is detected in this datacube. Most of the events appear to be located in the higher intensity regions, but this might be partially a selection effect, as the signal-to-noise ratio will be better in higher intensity regions.

In Figure 4(a), a histogram of the detected periodicities is shown, using a 5-s bin, where the periodicities inside the loop region (marked in Figure 2) have been excluded. The dashed line corresponds to the histogram for which the loop footpoint was included. There is a preference for the periodicity around 180 s, but apart from that, the periodicities picked up outside this loop are distributed fairly randomly. As expected, the main difference when the loop is included is in the periodicities between about 165 and 185 s. However, we do remind the reader here that only periods between 150 and 200 s are displayed. In Figure 4(b), the occurrence of patches of periodicity of a certain size is shown. To achieve a meaningful result, the size of an 'event' is calculated as the number of neighbouring pixels in which periodicity within a 10-s band is detected. For example, the plus signs correspond to periodicity patches between 150 and 160 s. The minimum size of

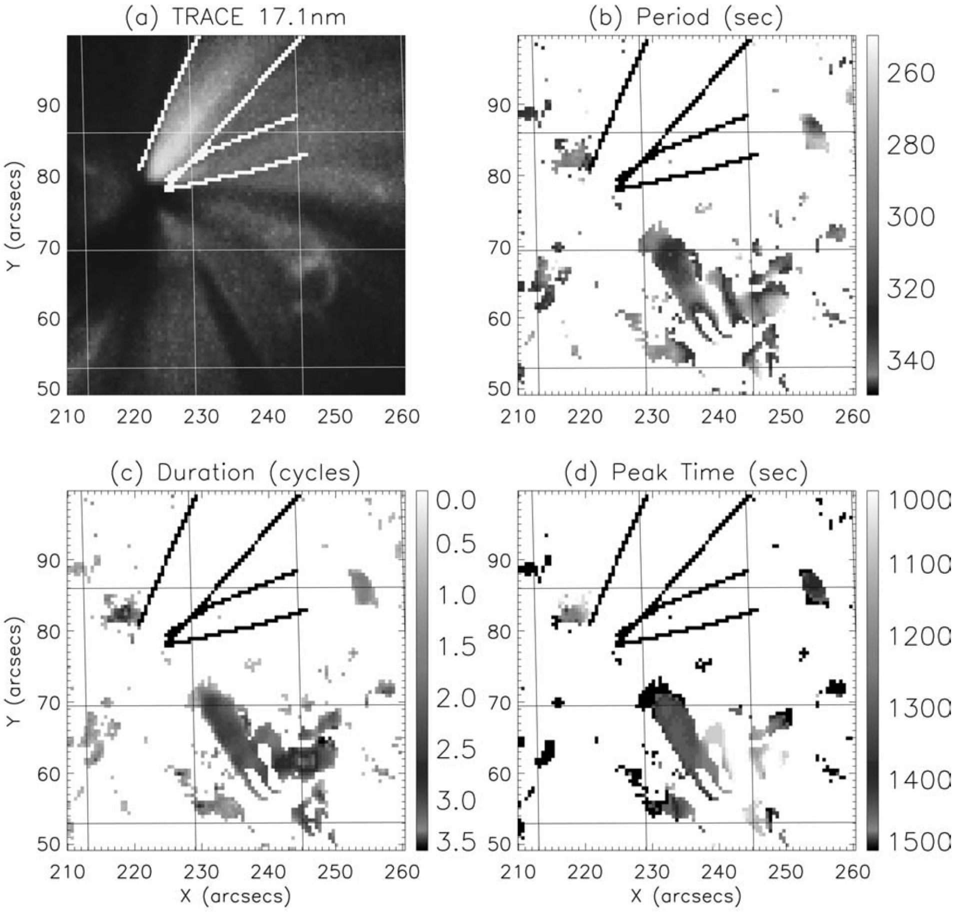

Figure 5. (a)-(d) Similar to Figure 2 but for the dataset taken at 06:46 UT on 13 June 2001.

an event has arbitrarily been set to 4 pixels, i.e., only events that are larger than 4 neighbouring pixels have been displayed. The single, large event (~ 30 pixels) corresponds to the 170–180 s periodicity that is detected inside the marked coronal structure. Indeed, when the periodicity inside the loop footpoint is excluded, this event is no longer present. All other events appear to be relatively small in size, with the majority consisting of less than 5 neighbouring pixels. Determining the size of these relatively short-lived events would be important if one tried to identify their nature and/or origin, i.e. if they had to be associated with one of the various categories of localised, burst-like events such as nanoflares or blinkers.

3.2. 13 June 2001

The second datacube we subject to the wavelet routine was taken at 06:46 UT on 13 June 2001, and consists of 64 100×100 ($0.5''$ pixel scale) TRACE 171 Å images.

The loops outlined in Figure 5(a) correspond to examples 17c and 17d in Paper I. Figure 5(b) shows the periodicities in the 150−400 s range, and it is immediately obvious that the situation is a lot more complicated than in Section 3.1. Unlike in the previous example, a substantial amount of larger 'patches' of coherent periodicities are found in this case and the short-lived, localised events appear to be absent.

First of all we look at the loops in which propagating intensity perturbations were detected in Paper I. From Figure 5(b) we see that, apart from at the edges of one of the loops (i.e., near the black lines), there are no obvious patches of periodicity inside the loops. However, the wavelet analysis in Paper I did pick up a quasi-periodic intensity disturbance, above a 99.0% confidence level. The most likely reason for this apparant contradiction is probaly the fact that, with a 0.5 arc sec resolution, the datacount, and thus the signal-to-noise ratio, is relatively low. Indeed, in the brightest part of the structure, the average (calibrated) datacount over the observed time interval is of the order of 170 DN/pixel, whereas in the 9 April 2000 dataset, the average datacount in the structure is of the order of 320 DN/pixel, which is considerably higher. In Paper I, the signal-to-noise ratio was artificially enhanced by summing over the pixels across the loop structures. The routine used in this study (spatially) smooths the data, but does not sum over pixels in any way. It is likely that the 'directional' summing (i.e., in the direction perpendicular to the wave propagation) in Paper I enhanced the intensity oscillations sufficiently to allow their detection by the wavelet analysis. Additonally, the smoothing of the data with a relatively large (5×5) boxcar has probably reduced the amplitude of any oscillations that might be present even further.

The other prominent feature in Figures 5(b–d) are the large patches of periodicity in the lower half of the image. These partially coincide with the bright, semi-circular feature that appears to be situated below the fan of large coronal loops. From Figure 5(c), we see that most of these periodicities last for about 2−3 cycles. From a movie of this datacube, it becomes apparent that these periodicities do not correspond to propagating intensity perturbations but to brightenings that occur at adjacent locations at different times. Indeed comparing Figures 5(b–d), it is clear that the periodicities occur simultaneously in relatively large areas, which indicates the brightening of a coronal structure, rather than a (propagating) intensity oscillation. Hence, by studying the time at which the periodicity is detected in a signal, the wavelet routine can also identify brightenings of a structure, as well as long-lived (propagating) intensity perturbations and short-lived, localised events.

4. Discussion and Conclusions

The main aim of this paper is to examine the possibility of automating the detection of solar oscillations, using wavelet analysis. Note here that 'detecting' does not imply that we have determined the nature or origin of events (apart from the oscillations already described in Paper I). The scope of this study is to demonstrate that wavelet analysis is capable of such detections. We subjected two datasets to the wavelet routine, with very different results. For the 9 April 2000 data, which has a relatively high datacount, the wavelet routine successfully picked up the long-lived intensity oscillation, labelled example 6a in Paper I. Once a coherent patch of periodicity was picked up, a (sustained) oscillation was mainly identified from the number of periodicity cycles. Apart from this periodic intensity perturbation, a lot of small-scale, short-lived periodicity was picked up. Although in this paper we are specifically looking for longer-lived, oscillations, identifying these short-lived events is an interesting study in itself. However, discussing the origin or nature of these small-scale events is beyond the scope of this paper. Besides, this would require a far more careful, detailed and structured treatment of the (removal of) noise in the data. Indeed, as pointed out several times before in this paper, the wavelet analysis will pick up any form of periodicity, including those caused artificially (e.g., by cosmic rays, spacecraft jitter, etc). We attempted to limit these by smoothing our datasets but if very localised events are of primary interest, this would probably not be desirable and more sophisticated approaches (e.g., a very careful alignment of the data) would be necessary. Despite these current limitations, we suggest that, by ‘training’ the wavelet routine in the correct way, it might be possible to study small-scale and/or short-lived events such as nanoflares or blinkers. As especially nanoflares are often linked to the background heating of the quiet corona, studying them on a large scale (i.e., in large areas and/or over long periods of time) could be an important and useful application of this automated wavelet routine.

In the second dataset (13 June 2001), a lot less small-scale periodicity was found, and the automated routine failed to detect the examples 17c and 17d of Paper I. Both these discrepancies are most likely caused by the lower datacount in this (higher-resolution) dataset. Unlike in Paper I, we did not sum in the direction perpendicular to the propagation to raise the signal-to-noise ratio. However, the analysis of this dataset did show that the wavelet routine can identify another phenomenon, namely the (simultaneous) brightenings within a coronal structure, as well as periodic intensity variations and burst-like events.

The analysis of these two datasets showed that, at present, the automation of the detection routine is only partial. The wavelet analysis will pick up any form of periodicity and it is up to the user to identify the physical context and relevance. One way to facilitate the identification of groups of coherent oscillations is reducing the periodicity range and then to repeat this procedure over all periodicities. Subsequently, the location of the periodicity has to be compared with an intensity image, to identify the coronal structure supporting it. Finally, a careful study of the detected period, the number of cycles and the timing is needed to determine the nature of the periodicity ‘patches’. Despite these current limitations, we believe that wavelet analysis can play an important role in the automation of data analysis and detection routines. For example, it is much faster to identify the coronal structure supporting periodicity detected by the wavelet routine, than to (manually) examine every single structure in a given dataset. Automated routines will considerably speed up the analysis of data and hence, make it possible to study much larger areas, for longer periods of time. Faster data analysis is both desirable, to improve the statistics of current results, and necessary, to be able to cope with the much larger quantity of data from future (solar) satellites.

We have demonstrated that, using the automated wavelet routine, one can easily distinguish between long-lived oscillations, burst-like events and brightenings of coronal structures. A possible extension to this study would be to investigate whether the wavelet routine can be 'trained' to identify other features found in the solar atmosphere. One would need to model the timeseries of such features, perform a wavelet analysis and see if this results in any unique characteristic parameters (e.g., period, duration, frequency spread, repeated oscillations, decay rate of wavelet power, etc.). It may be instructive to include spatial as well as temporal wavelet analysis here. If such a set of parameters, which uniquely describes a certain event, can be found, the detection of such an event in observational data could be automated using wavelet analysis.

Acknowledgements

RTJMCA acknowledges funding by the Leverhulme Trust via grant F00203/A. IDM acknowledges support from the Particle Physics and Astronomy Research Council. The authors are grateful to Dr. Craig DeForest for helpful discussion and suggestions. Wavelet software was provided by C. Torrence and G. Compo (http://paos.colorado.edu/research/wavelets).

References

Baudin, F., Bocchialini, K., and Koutchmy, S.: 1996, *Astron. Astrophys.* **314**, L9.

Berghmans, D. and Clette, F.: 1999, *Solar Phys.* **186**, 207.

Bocchialini, K. and Baudin, F.: 1995, *Astron. Astrophys.* **299**, 893.

Christopoulou, E. B., Skodras, A., Georgakilas, A. A., and Koutchmy, S.: 2003, *Astrophys. J.* **591**, 416.

De Moortel, I., Munday, S. A., and Hood, A. W., 2004, *Solar Phys.* , in press.

De Moortel, I., Ireland, J., Hood, A. W., and Walsh, R. W.: 2002, *Solar Phys.* **209**, 61.

Ireland, J., Walsh, R. W., Harrison, H. A., and Priest, E. R.: 1999, *Astron. Astrophys.* **347**, 355.

King, D. B., Nakariakov, V. M., Deluca, E. E., Golub, L., and McClements, K. G.: 2003, *Astron. Astrophys.* **404**, L1.

McAteer, R. J. T., Gallagher, P. T., Williams, D. R., Mathioudakis, M., Bloomfield, D. S., Phillips, K. J. H., and Keenan, F. P.: 2003, *Astrophys. J.* **587**, 806.

McAteer, R. J. T., Gallagher, P. T., Bloomfield, D. S., Williams, D. R., Mathioudakis, M., and Keenan, F. P.: 2004, *Astrophys. J.* **602**, 436.

McIntosh, S. W. and Smillie, D. G.: 2004, *Astrophys. J.* **604**, 924.

Molowny-Horas, R., Oliver, R., Ballester, J. L., and Baudin, F.: 1997, *Solar Phys.* **172**, 181.

Robbrecht, E., Verwichte, E., Berghmans, D., Hochedez, J. F., Poedts, S., and Nakariakov, V. M.: 2001, *Astron. Astrophys.* **370**, 591.

Torrence, C. and Compo, G. P.: 1998, *Bull. Amer. Meteor. Soc.* **79**, 61.

Ugarte-Urra, I., Doyle, J. G., Madjarska, M. S., and O'Shea, E. O.: 2004, *Astron. Astrophys.* **418**, 313.